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DEVELOPMENT AND ANALYSIS OF A GIS-BASED CURVE NUMBER MAP OF THE PHILIPPINES

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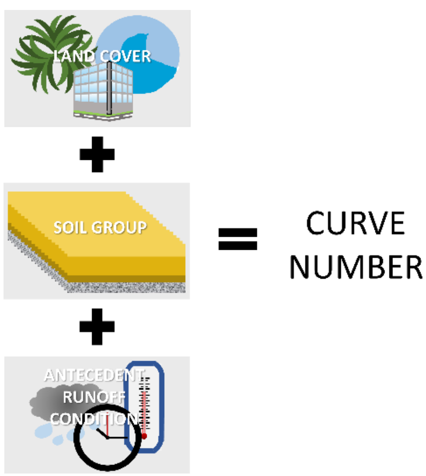
Graphical abstract



Abstract

Stormwater management requires quantitative methods to determine objective flood risk by estimating how much rainfall becomes runoff. With the absence of a locally generated runoff coefficient database in the Philippines, the standard model for surface runoff estimation is yet to be implemented using homegrown datasets. Traditionally, the empirical method is adapted from the National Resources Conservation Service (NRCS). The method quantifies rainfall-runoff relationships underscoring the combined effects of ground cover, soil hydraulic conductivity, and antecedent runoff condition (ARC) on runoff potential via a hydrologic parameter called the Curve Number (CN). Using geographic information system (GIS) tools, the Philippine CN map is developed by preprocessing and intersecting land use and land cover (LULC) and hydrologic soil group (HSG) with the CN look-up table. It was revealed that Group C soils dominate the Philippines. New data products—three raster CN maps at 25m spatial resolution—indicated the prevalence of medium to high runoff potential. National curve numbers were 61, 78, and 89 for dry, average, and wet ARCs, respectively. The outputs of this study provide access to spatially varied local runoff potential data in GIS format thus allowing direct GIS use for the swift simulation of flood damage mitigation models, among others.

Keywords: Curve number, geographic information system, hydrologic loss, runoff potential, hydrologic soil group

1.0 INTRODUCTION

1.1 Background

Several stormwater management methods are used in practice to estimate surface runoff. In particular, Thiam and Singh stressed that the National Resources Conservation Service (NRCS), formerly known as the Soil Conservation Service (SCS) of the United States Department of Agriculture (USDA), offers an empirical surface runoff estimation method leading to higher accuracy and time efficiency relative to other empirical and lumped parameter models—even when applied to ungauged watersheds [1]. This standard method relies on a lumped empirical parameter called the Curve Number (CN) hence the name NRCS-CN (formerly SCS-CN) method.

The NRCS under USDA crafted Part 650: Engineering Field Handbook of the National Engineering Handbook. Specifically on Chapter 2: Estimating Runoff Volume and Peak Discharge, the NRCS-CN method is discussed in detail—highlighting the effects of a pairwise dataset which includes land use and land cover (LULC) and hydrologic soil group (HSG) in the corresponding curve number [2].

In a review of the state of the hydrology practice, Hawkins, Ward, Woodward, and Van Mullem conceptualized CN as the watershed's hydrologic response as influenced by antecedent moisture condition (AMC), HSG, and LULC. The AMC, which is prefaced as the qualifier of soil moisture preceding a design storm event, induces the "observed spread of direct runoff around the central trend." AMC I, AMC II, and AMC III correspond to low, average, and high direct runoffs, where AMC II is taken as the assumed standard condition so conversion equations must be applied to obtain CN values for the other two. Currently, AMC is replaced with antecedent runoff condition (ARC) to also account for rainfall intensity and duration and temperature, among other "hydrologic error bands." HSG is categorized into four—Groups A to D—arranged from highest to lowest soil infiltration rates as indicated by the NRCS methodology [3]. Lastly, USDA describes land use in terms of various land management practices outlined in the National Engineering Handbook Part 630: Hydrology in Chapter 8: Land Use and Treatment Classes [4].

One of the primary challenges in hydrology is relating rainfall to runoff and vice-versa. These problems can be solved using various SCS methods such as SCS-CN and SCS Unit Hydrograph (SCS-UH) which are widely used in the Philippines be it in the public or private sector. Specifically, SCS or NRCS methods are useful in the following: 1) state-funded projects on flood risk assessment like Project Nationwide Operational Assessment of Hazards initially spearheaded by the Department of Science and Technology (DOST) [5]; 2) small-scale research studies on rainfall-runoff modeling for the catchments of Cebu Island [6]; and 3) due diligence in the industry sector as practiced by engineering consultancy firms.

Despite its wide usage, there is no existing CN database higher than 250m resolution for catchments all over the Philippines. As such, CN estimation largely remains manual, rendering the current practice time-consuming and prone to calculation errors especially when rushing to other phases of the project. To address the lack of a nationwide CN database that is readily available in the Philippines, this research aims to generate a gridded raster CN map of the whole Philippines for each ARC.

The study area is the Republic of the Philippines with geographical coordinates of 12.8797° North latitude and 121.774° East longitude [7].

By integrating a relatively novel geographic information system (GIS) approach to CN determination, hydrologists will benefit from the reduced workload and time which can be redirected to other phases of the project. Moreover, the salient features of this research revolve around ease of access to local hydrologic data for both HSG and CN database, richness in detail and variability of hydrologic data with local context, and overall efficiency due to digitalization—thereby promoting direct use for further GIS processing, and replicability for other planning scenarios concerning land use management for flood damage mitigation, for instance.

1.2 Standard Practice Limitations

Chin stressed that CN values based solely on HSG and LULC, and regional rainfall characteristics are strongly related. The study also revealed that intrastorm runoff rates obtained using the NRCS-CN method are only valid for high CN values since unrealistic runoff rates are obtained, exceeding actual infiltration capacities. Here, the CN method's shortcomings lie in ignoring the variability in regional rainfall trends which results in compromised accuracy for small-scale rainfall-runoff studies [8].

Stewart, Canfield, and Hawkins also showed that direct reliance on handbook and USDA-provided HSG data compromises accuracy as this practice results in CN values with a 1-HSG unit or 7-CN unit deviation relative to CN values derived from direct rainfall-runoff data [9]. Ultimately, it is crucial to assign HSGs based on said hydrologic data instead of relying on mere soil texture survey.

1.3 LULC and HSG Effects

A study conducted by Rietz and Hawkins highlighted that for roughly all land uses of interest, significant differences in CN values were found at 5% level. This difference between the measured and modeled CN values is attributed to the latter's assumption that soil type and cover density are constant. Other factors that drive this CN value deviation includes, among others the following: local climate, whether the watershed is grazed or ungrazed, and history of land use conversion. Variability in CN values was observed the highest in forested lands but rather insignificant in agricultural watersheds [10].

Land use and geomorphological changes occur alongside urbanization and development. Specifically, urbanized areas lead to larger impervious areas. Ogden, Pradhan, Nelson, and Downer developed a physics-based model that was found to perform great, even without calibration, in simulating the complexities of the effects of changing land uses in the CN value. In their study, Gridded Surface/Subsurface Hydrologic Analysis (GSSHA) model was used to simulate heterogeneities in land use, land surface and subsurface, and hydrologic parameters like soil saturated hydraulic conductivity, roughness, porosity, initial moisture content and capillary head [11]. The use of GIS is then encouraged over the adaptation of manual CN calculations.

1.4 Mapping Tools

A global CN map having a resolution higher than 0.1° was yet to be available so Jaafar, Ahmad, and El Beyrouthy attempted to generate one at 250m resolution using an open-source R script [12] to process the land cover classes from the European Space Agency [13] that were mapped into NEH-630 classes and the hydrologic soil group global data product [14]. Results indicate that the dominant global runoff potential is medium to high with CN values between 75 and 85 [12].

Meanwhile, Merwade modeled CN determination using land cover and soil data on ArcGIS with spatial analyst extension tools. The raster LULC map underwent reclassification for the reduction of layers. Next, a dominant soil code (HSG) was assigned to the feature class. ArcTool box's Union tool was then used to merge the input maps to produce polygons containing both LULC and HSG information. ArcCatalog was used to set up the CN look-up table which was then intersected with the merged LULC-HSG polygon to generate the gridded CN map [15].

Another GIS-based model simulation was performed by Karnika and Tripathi to generate a CN map in raster format which was made possible by Arc Hydro Tool and Geospatial Hydrologic Modeling Extension (HEC-Geo HMS 10.3). There were four categories of LULC, namely water, forest, medium residential and agriculture, as taken from the Anderson land use classification system [16].

2.0 METHODOLOGY

This research is a case study investigating the effect of land use or land cover and soil type in Philippine catchments on the respective runoff potentials of these areas. The CN grid generation phase used QGIS 3.3 s-Hertogenbosch as it is a free open-source GIS platform thus allowing for ease of access among the general public.

The schematic of the development of the Philippine curve number grid is shown in Figure 1. All raw data used are the latest government-issued digital information open for public use.

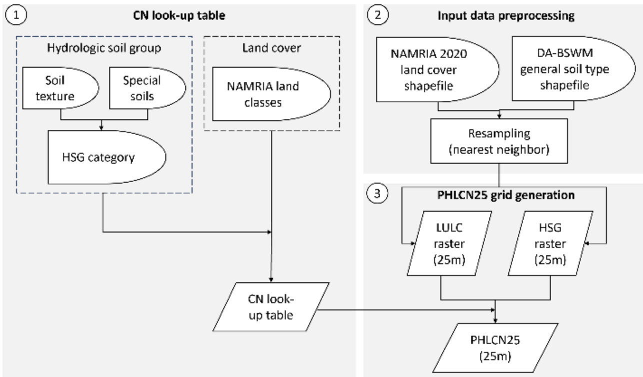


Figure 1 Schematic of the Philippine curve number map generation process

2.1 Preparation of Land Cover Map

Land cover data was taken from the 2020 National Mapping and Resource Information Authority (NAMRIA) land cover polygon shapefiles [17] which were extracted thru Geoportal Philippines. The land classes from NAMRIA were benchmarked against the National Land Cover Data (NLCD) dataset [18] developed by the Multi-Resolution Land Characteristics Consortium in the US. This was done to ensure compliance with NRCS standards. To create a standard and process-efficient model for the LULC classification scheme, each NAMRIA land class was matched to the comparable NLCD class(es) which resulted in the reduction of the number of LULC layers to be processed.

Since the local land cover classification system generally conforms to standard NLCD classes, no reclassification is required for the raw LULC data. It follows that from the numerous NLCD-based gridcodes with the same general description, the similar NAMRIA land class was assigned to a single unique gridcode—thereby enabling the systematic implementation of the employed local LULC classification scheme. The descriptions and corresponding codes of NAMRIA-based and the comparable NLCD land classes are presented in Table 1.

Table 1 Benchmarked NAMRIA-based LULC classes and codes *(Source: MRLC, 2001; Dag-uman, 2022)*

NLCD Land Classes	LULC Code	NAMRIA Land Classes	LULC Code
Description	Gridcode	Description	Gridcode
Barren land	31	Open/Barren	1
Planted/Cultivated	81, 82	Annual Crop	2
Grassland/Herbaceous	71	Grassland	3
Planted/Cultivated	81, 82	Perennial Crop	4
Developed	21-24	Built-up	5
Open Water	11	Fishpond	6
Wetlands	96-99	Mangrove Forest	7
Shrubland	51, 52	Brush/Shrubs	8
Open Water	11	Inland Water	9
Forest	41, 42, 43	Closed Forest	10
		Open Forest	11
Wetlands	90-99	Marshland/Swamp	12

2.2 Creation of Hydrologic Soil Group Map

The general soil type data was taken from the Bureau of Soils and Water Management under the Department of Agriculture (DA-BSWM). The general soil type polygon shapefile [19] was extracted thru Geoportal Philippines. Additionally, the HSG classification system in Table 2 is based on the USDA wherein a total of four soil groups are distinguished by their respective infiltration capacities [20] since the said hydrologic parameter is reflective of the physical properties of certain soil types. Description of potential soil types under each soil group is also provided.

Table 2 NRCS-based hydrologic soil group according to infiltration rate *(Source: USDA, 2009)*

Group	Infiltration Rate [in/hr]	Soil Type Description
A	0.30-0.45	High infiltration rates. Deep, well-drained sands and gravels.
B	0.15-0.30	Moderate infiltration rates. Moderately deep, moderately well-drained soils with moderately coarse textures.
C	0.05-0.15	Slow infiltration rates. Soils with layers, or soils with moderately fine textures.
D	0.00-0.05	Very slow infiltration rates. Clayey soils, high water table, or shallow impervious layer.

Another way to group soil types into the said HSGs is to cluster them into the appropriate soil textures. In particular, the USDA has released a guide to estimate the corresponding HSG type of various textural soils in accordance with the USDA soil texture nomenclature which includes coarse, moderately coarse, moderately fine, and fine textured soils [20]. This matrix also factors in the effects of growing impervious area in many lands mainly due to urbanization and rapid development. Table 3 summarizes the employed HSG reclassification matrix according to soil texture.

Table 3 Hydrologic soil group reclassification matrix by soil texture *(Source: USDA, 2009)*

DA-BSWM Classification	Revised Classification	
Description	HSG	Value
Sand	A	1
Loamy sand	B	2
Sandy loam		
Loam	C	3
Silty loam		
Silt		
Clay loam		
Sandy clay loam		
Silty clay loam		
Sandy clay	D	4
Silty clay		
Clay		

Furthermore, there also exist soils that require further investigation in order to determine the corresponding HSG type. In the context of this study, they are hereinafter referred to as special soils. Special soils include soil types in the Philippines that are not explicitly texturized as well as those with remarkable drainage conditions or situated in environments with unique hydrology thereby affecting the governing in-situ soil infiltration trends. In the development of the HSG reclassification matrix for special soils (Table 4), mixed literature was consulted, and the corresponding infiltration potential was then inferred to finally arrive at a suitable HSG type. One noteworthy consideration was taken from the book of Philippine soils by Carating et al. which discussed the close proximity of some soils to water bodies including hydrosols and beach and river sands [21].

For conservative results, soil items that fall under the dual hydrologic soil groups are reduced to HSG D to indicate the slowest infiltration rates and thus, highest runoff potentials.

Table 4 Hydrologic soil group reclassification matrix for special soils

DA-BSWM Classification	Revised Classification	
Description	HSG	Value
Rock/rough stony/rough broken/rubble land	A	1
Complex	C	3
Filled up soil		
Mountainous land		
Undifferentiated soil	D	4
Tarlac soil		
Beach sand	A/D	
Peat		
River sand		
Lava	B/D	
Sabangan soil		
Clay loam adobe	C/D	
Hydrosol	D/D	

2.3 Generation of Curve Number Grid

Since the USDA-provided handbook CN lookup tables were found to result in CN values with a 1-HSG or 7-CN unit deviation from direct rainfall-runoff data, third-party watershed hydrologic studies were consulted to determine the more appropriate lookup table to be used in the Philippine setting. Studies by Quijano et al. [22] and Cayson, Patiño, and Flores [6] both employed a simplified CN lookup table assuming an average ARC and an initial loss equal to 20% of storage. This lookup table presented in Table 5 shows that a unique curve number exists for each LULC-HSG pair. CN values range from 0 to 100 indicating the lowest to highest runoff potential, respectively.

Table 5 Curve number lookup table for LULC-HSG pairs *(Source: Quijano et al., 2015)*

Land Use/Land Cover	Curve Number for Various HSGs			
Description	A	B	C	D
Open/Barren	63	77	85	88
Annual Crop	67	78	85	89
Grassland	30	58	71	78
Perennial Crop	45	66	77	83
Built-up	89	92	94	95
Fishpond	99	99	99	99
Mangrove Forest	98	98	98	98
Brush/Shrubs	30	48	65	73
Inland Water	99	99	99	99
Closed Forest	30	55	70	77
Open Forest	36	60	79	79
Marshland/Swamp	72	81	88	91

The preprocessed LULC and HSG data were then intersected with the CN look-up table through the Geospatial Data Abstraction Library (GDAL) raster calculator in QGIS to generate the CN map for average ARC. The CN lookup table in Table 5 was coded using GDAL raster calculator. The GDAL numeric syntax for the generation of the curve number grid map for average ARC is given by the code shown in Figure 2.

```
99*(A==9) + 99*(A==6) + 98*(A==7) + 89*logical_and(A==5, B==1)
+ 92*logical_and(A==5, B==2) + 94*logical_and(A==5, B==3)
+ 95*logical_and(A==5, B==4) + 72*logical_and(A==12, B==1)
+ 81*logical_and(A==12, B==2) + 88*logical_and(A==12, B==3)
+ 91*logical_and(A==12, B==4) + 67*logical_and(A==2, B==1)
+ 78*logical_and(A==2, B==2) + 85*logical_and(A==2, B==3)
+ 89*logical_and(A==2, B==4) + 63*logical_and(A==1, B==1)
+ 77*logical_and(A==1, B==2) + 85*logical_and(A==1, B==3)
+ 88*logical_and(A==1, B==4) + 45*logical_and(A==4, B==1)
+ 66*logical_and(A==4, B==2) + 77*logical_and(A==4, B==3)
+ 83*logical_and(A==4, B==4) + 36*logical_and(A==11, B==1)
+ 60*logical_and(A==11, B==2) + 79*logical_and(A==11, B==3)
+ 79*logical_and(A==11, B==4) + 30*logical_and(A==3, B==1)
+ 58*logical_and(A==3, B==2) + 71*logical_and(A==3, B==3)
+ 78*logical_and(A==3, B==4) + 30*logical_and(A==10, B==1)
+ 55*logical_and(A==10, B==2) + 70*logical_and(A==10, B==3)
+ 77*logical_and(A==10, B==4) + 30*logical_and(A==8, B==1)
+ 48*logical_and(A==8, B==2) + 65*logical_and(A==8, B==3)
+ 73*logical_and(A==8, B==4)
```

where
A: land use-land cover gridcode of a single grid in the LULC raster
logical_and(): numpy array function for intersecting LULC and HSG
B: hydrologic soil group value of a single grid in the HSG raster

Figure 2 Setting up the CN look-up table using GDAL syntax

Conversion from CN II to CN I and from CN II to CN III maps were then performed with the aid of empirical conversion equations from NRCS using Equation 1 and Equation 2 [3], respectively.

$$CN(I) = \frac{4.2CN(II)}{10 - 0.058CN(II)} \tag{1}$$

where

CN (I): curve number for dry antecedent runoff condition (dimensionless)

CN (II): curve number for average antecedent runoff condition (dimensionless)

The GDAL numeric syntax for the conversion from CN II to CN I is given by:

(4.2*A)/(10-0.058*A)

where

A: curve number value of a single grid of the CN II raster

$$CN(III) = \frac{23CN(II)}{10 + 0.13CN(II)} \tag{2}$$

where

CN (II): curve number for average antecedent runoff condition (dimensionless)

CN (III): curve number for wet antecedent runoff condition (dimensionless)

The GDAL numeric syntax for the conversion from CN II to CN III is given by:

(23*A)/(10+0.13*A)

where

A: curve number value of a single grid of the CN II raster

3.0 RESULTS AND DISCUSSION

3.1 Preprocessed Input Rasters

After merging the raw regional land cover shapefiles, conversion from feature class to raster ensued. Using ArcGIS Spatial Analyst extension and the raw LULC map as the input raster, the local land class symbology shown in Table 1 was adapted to categorize ground cover into standard-conforming themes. This process yielded an LULC raster at 25m spatial resolution as shown in Figure 3. Results indicate that perennial crop and open forest dominate the land cover map of the Philippines.

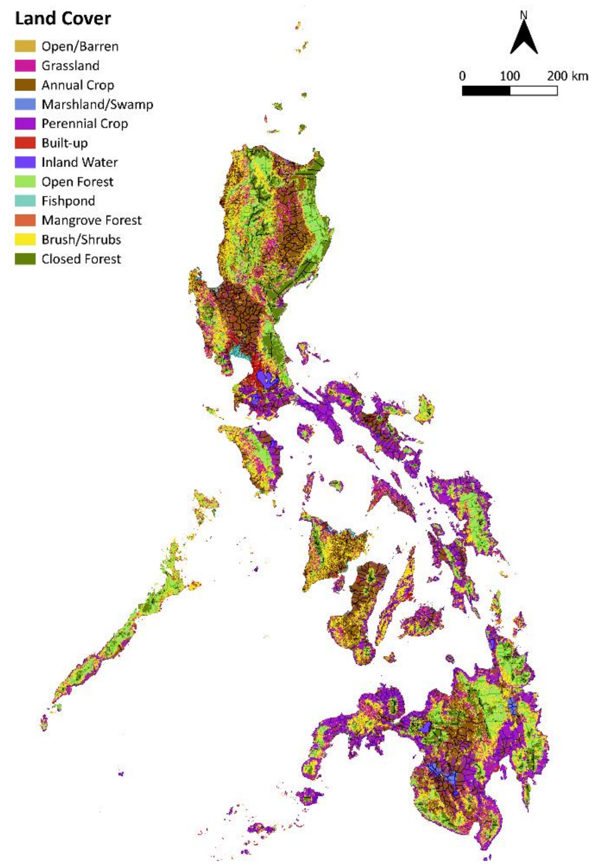


Figure 3 Gridded raster LULC map of the Philippines

Similar to the raw land cover data, the raw soil data was rasterized using the Conversion Tool. The soil raster was then reclassified using the matrices shown in Table 3 and Table 4 with soil type as the reclass field. The output HSG raster was generated at 25m spatial resolution as shown in Figure 4.

In comparison to the clipped global HSG map at 250m resolution (HYSOGs250m) developed by Ross et al. [14], the generated HSG maps at 25m resolution show more detail in that the locally generated maps show Groups A and B which were likely reduced to dual classification in the global map since it utilized soil texture predictions only instead of actual field data. Moreover, all three maps show that the two dominant HSG types are Groups C and D, with the global and modified local HSG maps both indicating the prevalence of Group C soils, thus justifying the employment of a modified HSG matrix with urbanization effects.

Figure 4 Gridded raster HSG map of the Philippines

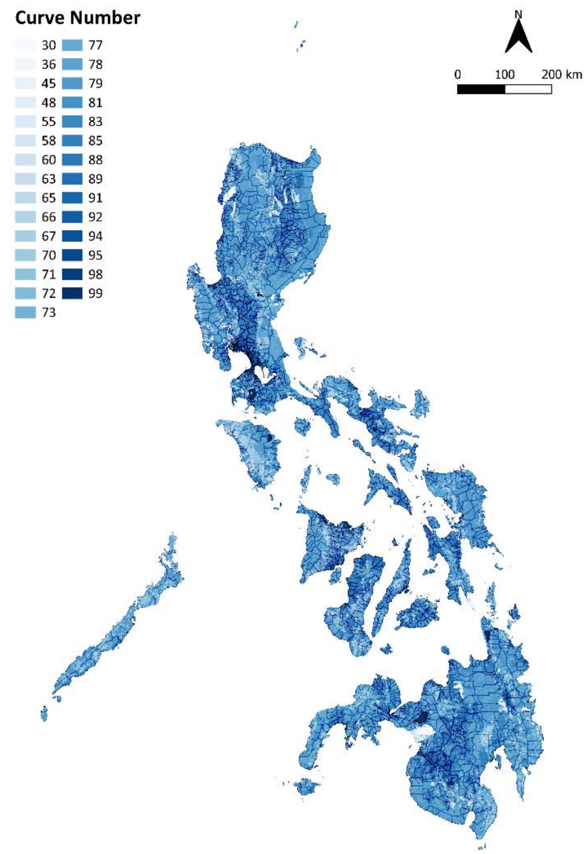


Figure 5 Curve number grid of the Philippines for average ARC

3.2 Output Curve Number Maps

The Philippine curve number grid for average ARC (ARC II) was generated by setting the input rasters in the GDAL calculator to the following: LULC raster as layer A, and HSG raster as layer B. For convenience, the output raster used was integer-type. An image of the CN II map of the Philippines at 25m spatial resolution is shown in Figure 5.

Similarly, raster calculations were also performed here using GDAL-coded syntax of the CN conversion Equation 1 and Equation 2 with CN II grid as layer A for both conversion processes. The resulting CN I and CN III maps of the Philippines at 25m spatial resolution are shown in Figure 6 and Figure 7, respectively.

Results indicated that the mean curve numbers for CN I, CN II, and CN III were 61, 78, and 89, respectively. These values show that medium to high runoff potential dominates the Philippines. Highest curve numbers were concentrated in areas such as the National Capital Region (NCR), Central Mindanao, and some parts of Northern Luzon, Central Luzon, Western Visayas, and Bicol. Summarized in Table 6 is the technical validation of generated curve numbers for the three antecedent runoff conditions.

Table 6 Technical validation of generated curve numbers

ARC	Alcober & Macuha, 2024				Jaafar et al., 2019			
	min	max	μ^a	σ^b	min	max	μ^a	σ^b
dry	15	98	61	12.7	36	81	57	4.6
ave	30	99	78	9.3	56	92	76	3.6
wet	50	100	89	5.9	75	97	89	2.2

[a]CN spatial mean

[b]CN spatial standard deviation

Relative to the global curve number estimates at 250m spatial resolution (GCN250) developed by Jaafar et al. (2019), the generated local CN values at 25m spatial resolution (PHLCN25) by Alcober & Macuha (2024) resemble that of the global scenario. The calculated curve numbers in the current study show a deviation of +4 and +2 CN units from GCN250 values in terms of the CN spatial mean for CN I (dry ARC) and CN II (average ARC), respectively. Meanwhile, there is no difference between the spatial mean global and local CN III (wet ARC). Also, local CN values show a much wider range than their global counterparts owing to the rich spatial heterogeneity of the former's soil data with local context. Generally higher runoff potential was obtained in this research due to conservative estimates like employing the modified HSG reclassification matrix with urbanization effects, as well as the reduction of dual HSG soils into Group D.

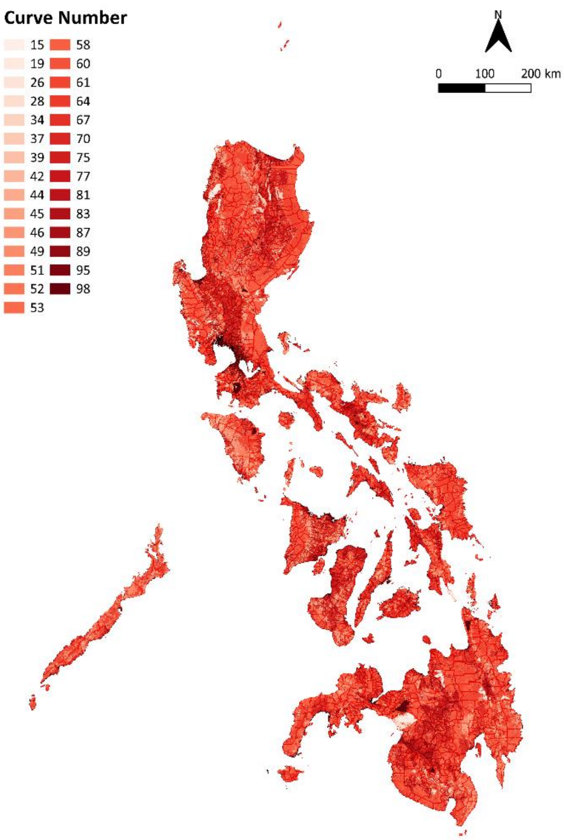


Figure 6 Curve number grid of the Philippines for dry ARC

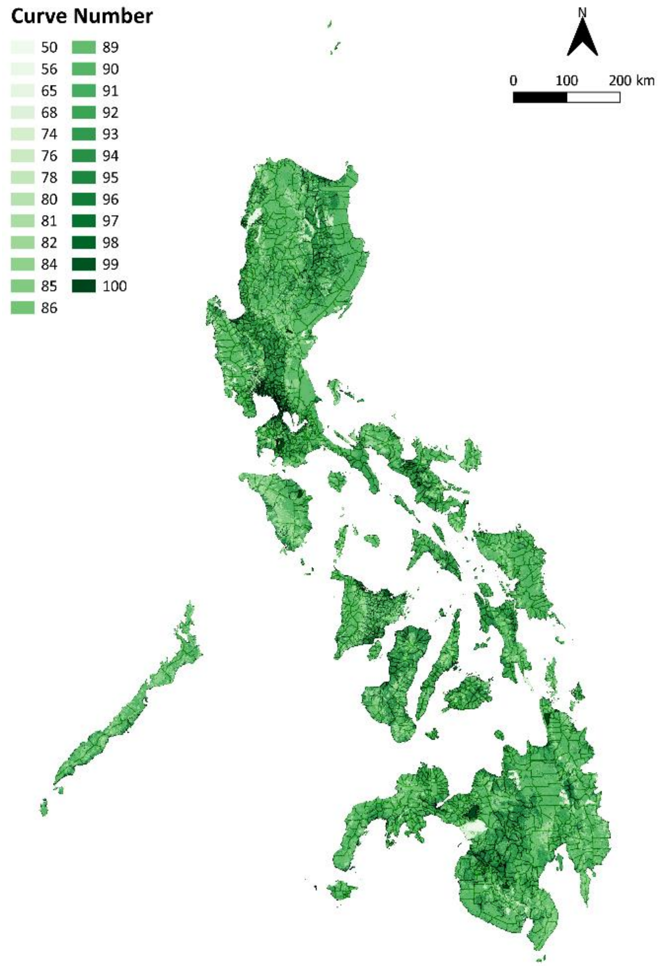


Figure 7 Curve number grid of the Philippines for wet ARC

3.3 File Availability

The raw data, preprocessed input LULC and HSG maps, and the curve number raster files generated in this study can all be accessed in GIS format by visiting this repository: bit.ly/phlcn25 which also includes raw data for technical validation, full matrix of Philippine soils and their corresponding HSG assignments, and an instruction manual on generating GIS-based CN grids using Philippine-specific datasets. Alternatively, scan the quick response (QR) code shown in Figure 8.

SCAN ME

Figure 8 QR code for the link to PHLCN25 data products repository

4.0 CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

Stormwater management requires quasi-quantitative methods to determine objective flood risk assessment by relating rainfall and runoff. Exceedance of soil infiltration capacity by the rate of rainfall causes overland flow which may result in flooding at alarming surface runoff levels. To estimate how much rainfall becomes runoff, a lumped hydrologic parameter called the Curve Number (CN) is used. A standard framework from the NRCS is adapted to empirically quantify rainfall-runoff relationships which underscores the combined effects of land use, soil hydraulic conductivity, and antecedent runoff condition on the runoff potential of catchments as represented by the empirical constant, CN.

The key findings of this study are as follows:

- Using a modified HSG reclassification matrix factoring in the effects of urbanization and growing impervious land area, the dominant HSG type in the Philippines is Group C, which conforms with the existing clipped global HYSOGs250m.
- The local curve numbers were 61, 78, and 89 for dry, average, and wet antecedent runoff conditions, respectively. Medium to high runoff potential dominates the Philippines. Specifically, high runoff potentials are observed in the National Capital Region (NCR), Central Mindanao, and some parts of Northern Luzon, Central Luzon, Western Visayas, and Bicol.

The calculated curve numbers show a maximum of 4-CN unit deviation from the mean GCN250 values, with the CN under dry antecedent runoff condition showing the biggest difference. Relative to the existing CN database, a higher range of runoff potential was observed since more spatially varied land cover and soil data were utilized. Rather than employing data predictions, the current research processed actual field data validated by local experts through in-situ surveys. Finally, the spatial resolution of the output maps is a hundred times better than that of existing maps—from 250m x 250m to 25m x 25m grids.

4.2 Recommendations

Room for improvements in this study may be accomplished in future researches. These include the following:

- Calibrate a curve number generator model using historical hydrologic data throughout the Philippines.
- Estimate the impervious area of several land areas and incorporate it into the CN lookup table.
- Use a more detailed soil survey map to offset the uncertainty caused by undifferentiated soils in the generation of CN values.
- Utilize quantitative soil infiltration rates in order to generate a more objective hydrologic soil group map of the Philippines.
- Integrate infiltration rate data with depth to bedrock and depth to groundwater table in the criteria for the assignment of hydrologic soil groups.

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